

# Reconocimiento de Patrones

Version 2024-I

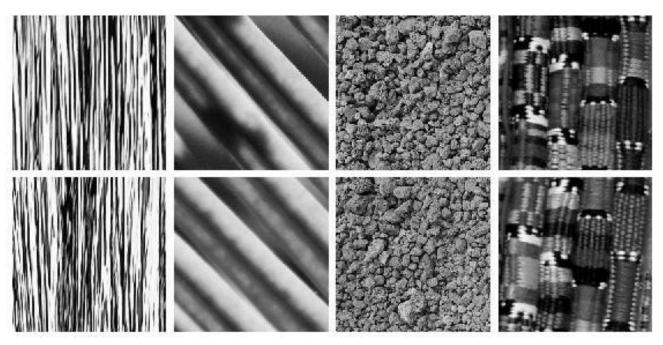
## Texturas de Haralick

[Capítulo 2]

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DSP-ASIC BUILDER GROUP Director Semillero TRIAC Ingenieria Electronica Universidad Popular del Cesar

## Different Textures →



# What are texture images?

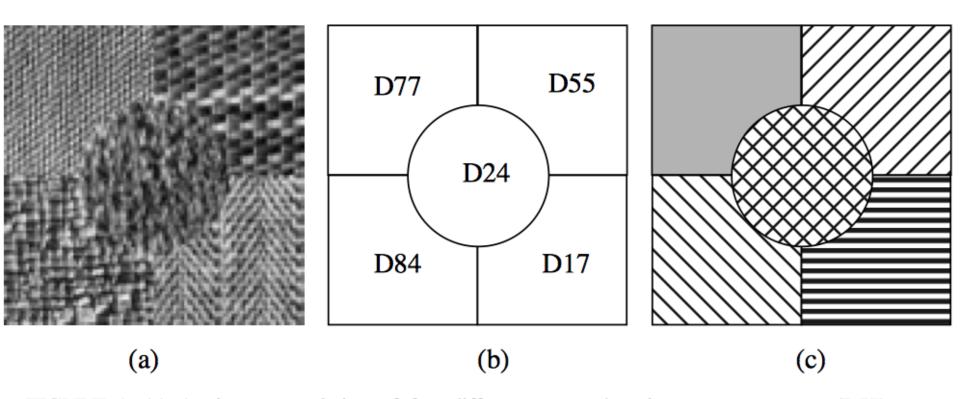


FIGURE 1. (a) An image consisting of five different textured regions: cotton canvas (D77), straw matting (D55), raffia (D84), herringbone weave (D17), and pressed calf leather. [8]. (b) The goal of texture classification is to label each textured region with the proper category label: the identities of the five texture regions present in (a). (c) The goal of texture segmentation is to separate the regions in the image which have different textures and identify the boundaries between them. The texture categories themselves need not be recognized. In this example, the five texture categories in (a) are identified as separate textures by the use of generic category labels (represented by the different fill patterns).

<u>The Handbook of Pattern Recognition and Computer Vision (2nd Edition)</u>, by C. H. Chen, L. F. Pau, P. S. P. Wang (eds.), pp. 207-248, World Scientific Publishing Co., 1998.

# Co-occurrence matrices They measure how is the distribution of co-occurring of pairs of pixels in an image.

Haralick, R.M., K. Shanmugan, and I. Dinstein (1973): <u>Textural Features for Image Classification</u>, IEEE Transactions on Systems, Man, and Cybernetics, SMC-3:610-621.

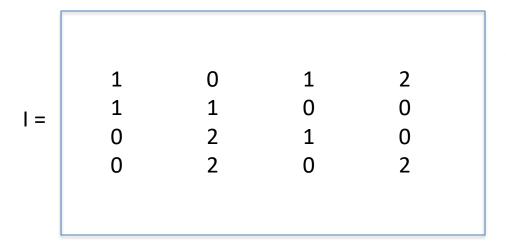
They measure how is the distribution of co-occurring of pairs of pixels in an image.

## Example:

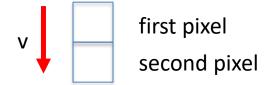
They measure how is the distribution of co-occurring of pairs of pixels in an image.

## Example:

Given an imagen I, the co-ccurrence matrix  $P_{10}$  is computed as follows:



10 indicates 1  $\Psi$  and 0  $\rightarrow$ :

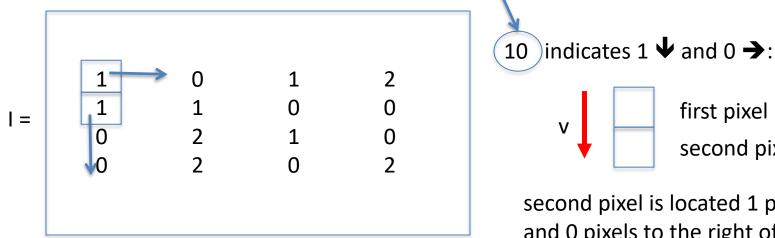


second pixel is located 1 pixel down, and 0 pixels to the right of the first pixel.

They measure how is the distribution of co-occurring of pairs of pixels in an image.

## Example:

Given an imagen I, the co-ccurrence matrix  $P_{10}$  is computed as follows:



first pixel

second pixel

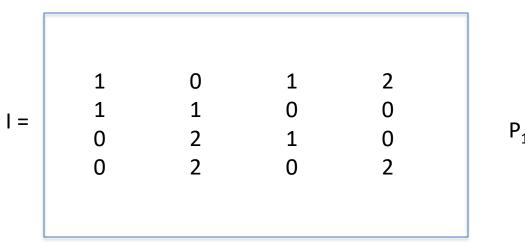
second pixel is located 1 pixel down, and 0 pixels to the right of the first pixel.

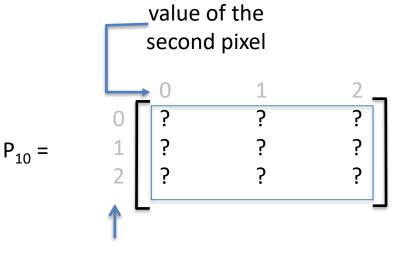
For direction 10, there are 12 possible pairs pixels that can be analized.

They measure how is the distribution of co-occurring of pairs of pixels in an image.

## Example:

Given an imagen I, the co-ccurrence matrix  $P_{10}$  is computed as follows:

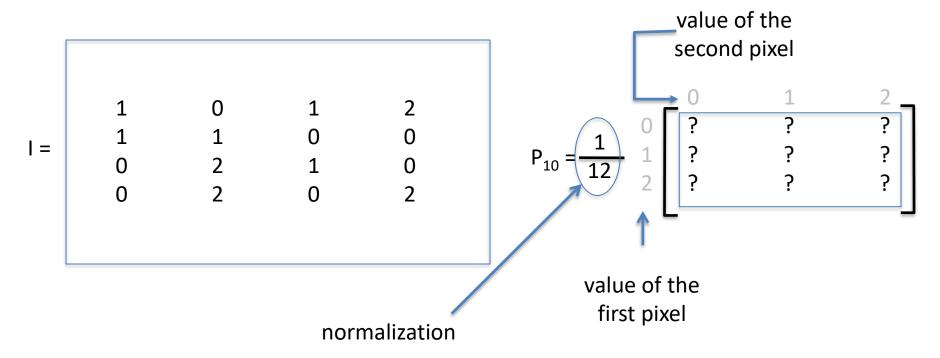




value of the first pixel

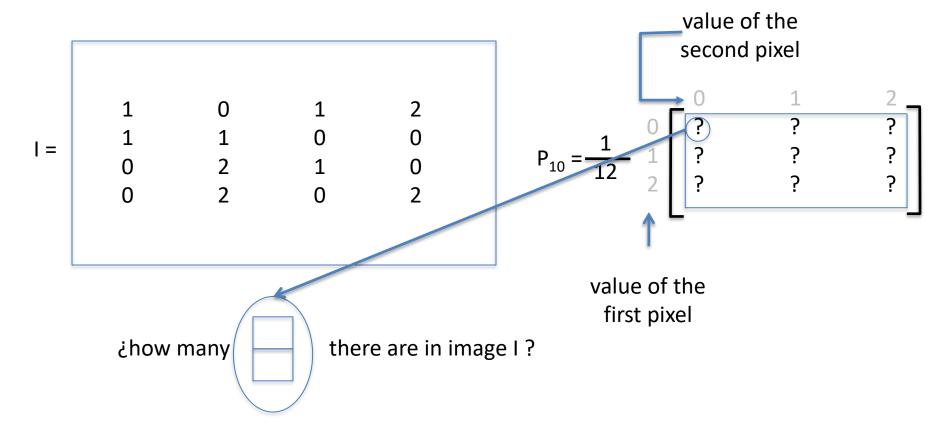
They measure how is the distribution of co-occurring of pairs of pixels in an image.

## Example:



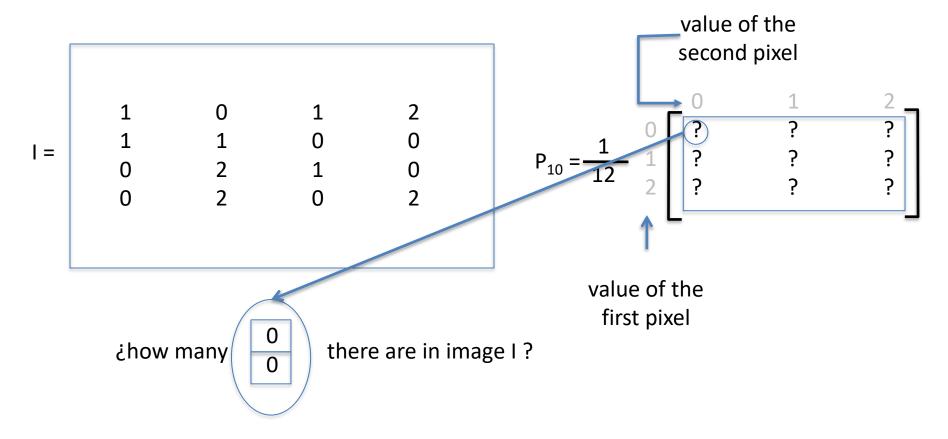
They measure how is the distribution of co-occurring of pairs of pixels in an image.

## Example:



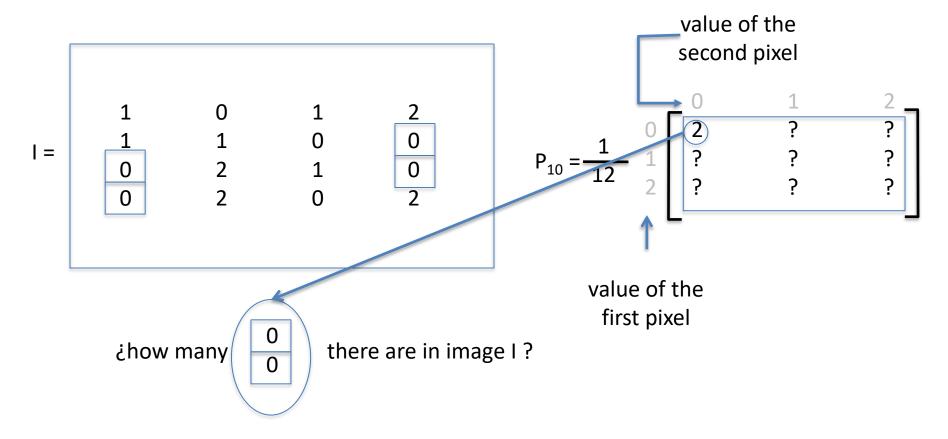
They measure how is the distribution of co-occurring of pairs of pixels in an image.

## Example:



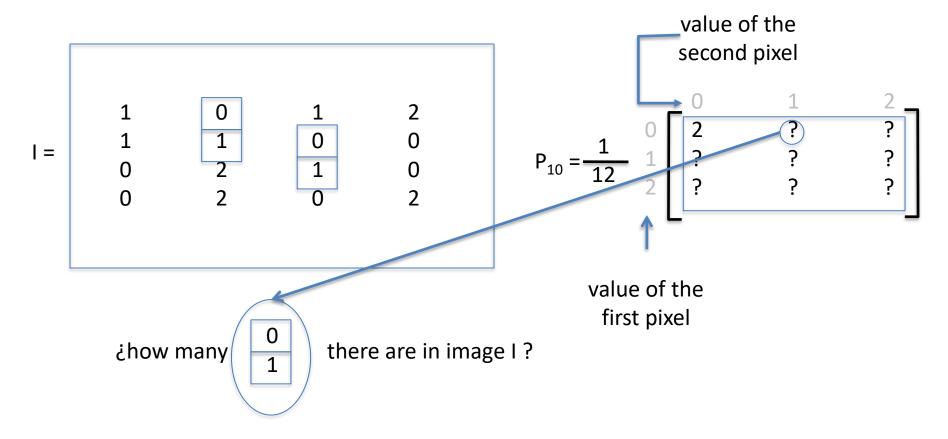
They measure how is the distribution of co-occurring of pairs of pixels in an image.

## Example:



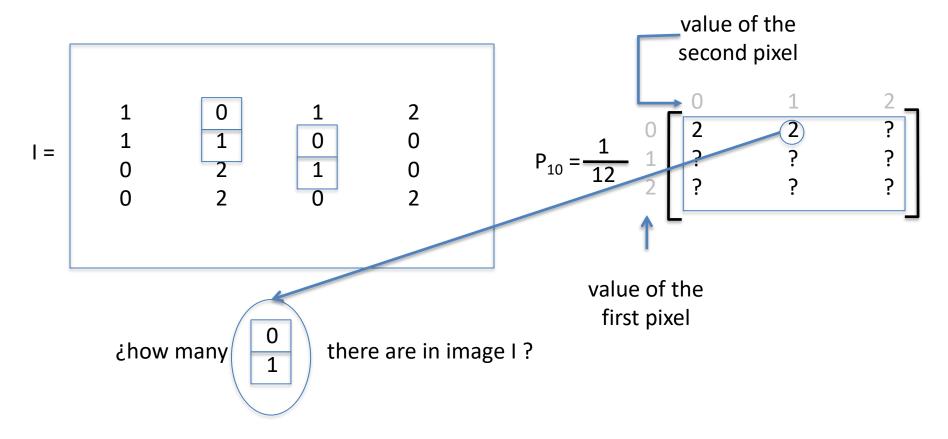
They measure how is the distribution of co-occurring of pairs of pixels in an image.

## Example:



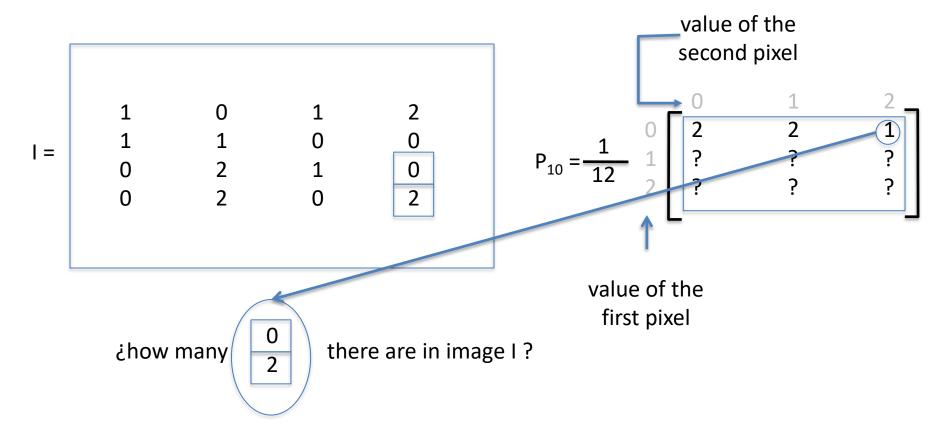
They measure how is the distribution of co-occurring of pairs of pixels in an image.

## Example:



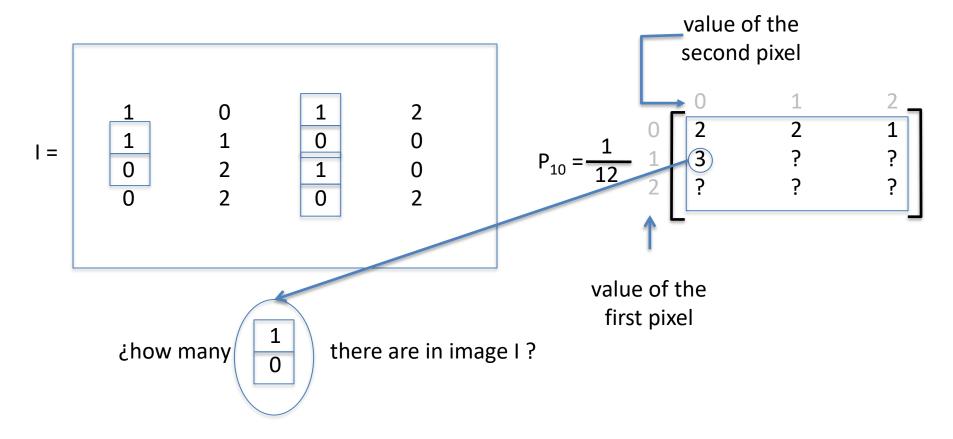
They measure how is the distribution of co-occurring of pairs of pixels in an image.

## Example:



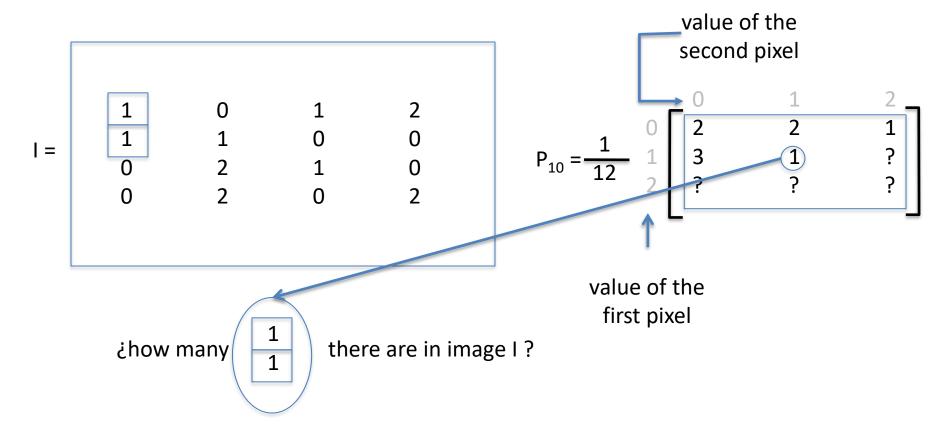
They measure how is the distribution of co-occurring of pairs of pixels in an image.

## Example:



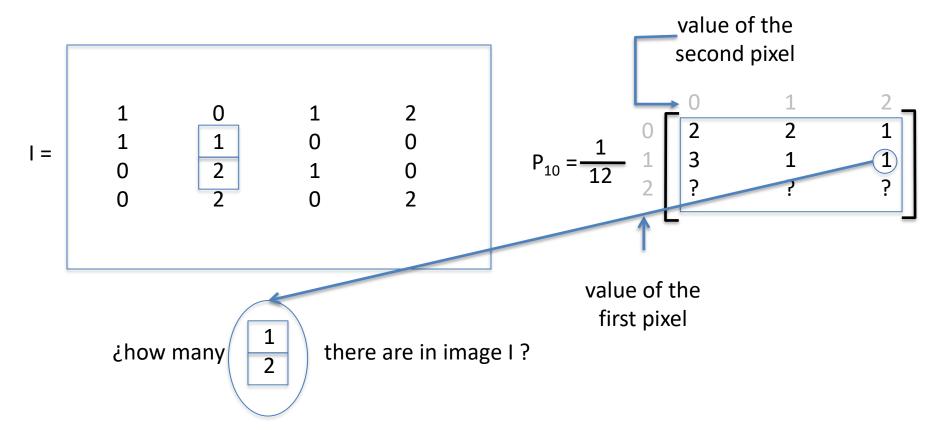
They measure how is the distribution of co-occurring of pairs of pixels in an image.

## Example:



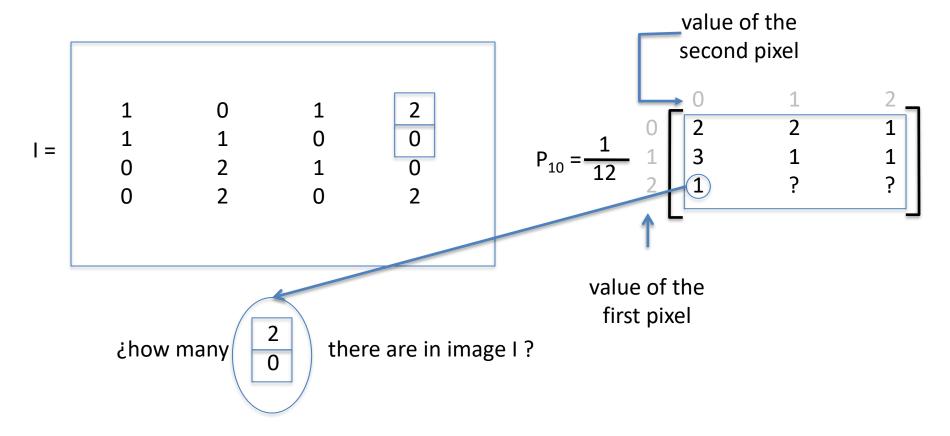
They measure how is the distribution of co-occurring of pairs of pixels in an image.

## Example:



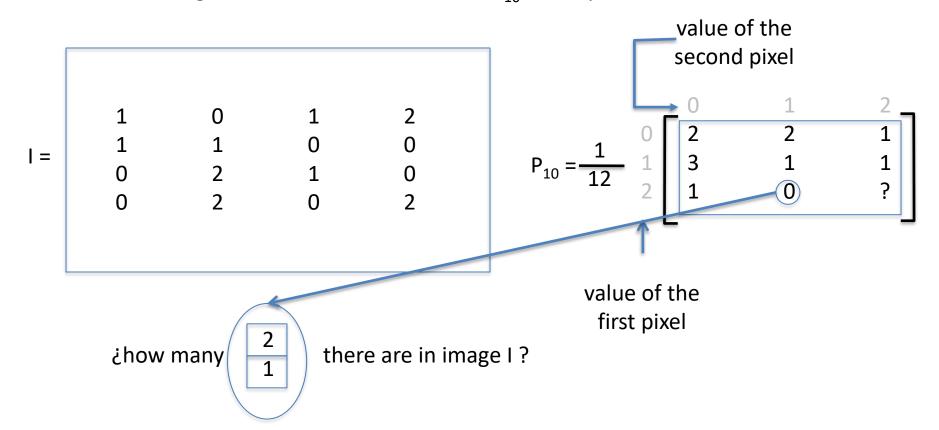
They measure how is the distribution of co-occurring of pairs of pixels in an image.

## Example:



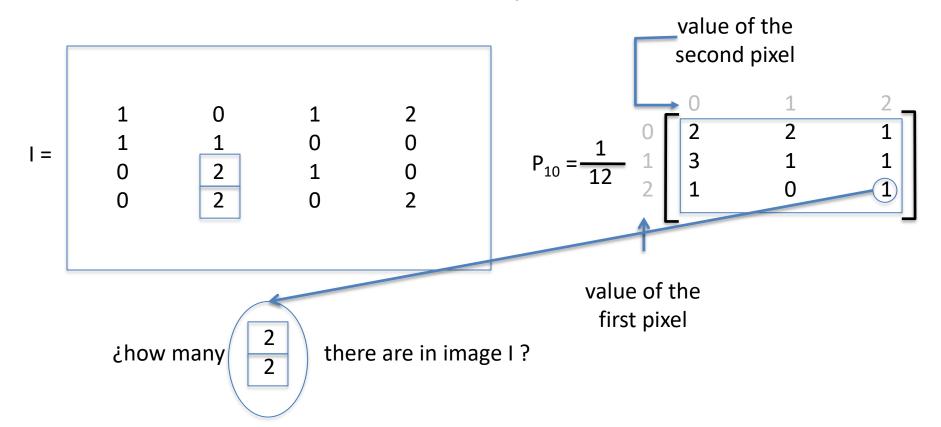
They measure how is the distribution of co-occurring of pairs of pixels in an image.

## Example:



They measure how is the distribution of co-occurring of pairs of pixels in an image.

## Example:



They measure how is the distribution of co-occurring of pairs of pixels in an image.

## Example:

Given an imagen I, the co-ccurrence matrix  $P_{10}$  is:

$$I = \begin{bmatrix} 1 & 0 & 1 & 2 \\ 1 & 1 & 0 & 0 \\ 0 & 2 & 1 & 0 \\ 0 & 2 & 0 & 2 \end{bmatrix}$$

They measure how is the distribution of co-occurring of pairs of pixels in an image.

Example:

Given an imagen I, the co-ccurrence matrix  $P_{11}$  is:

$$I = \begin{bmatrix} 1 & 0 & 1 & 2 \\ 1 & 1 & 0 & 0 \\ 0 & 2 & 1 & 0 \\ 0 & 2 & 0 & 2 \end{bmatrix}$$



They measure how is the distribution of co-occurring of pairs of pixels in an image.

Example:

Given an imagen I, the co-ccurrence matrix  $P_{11}$  is:

$$I = \begin{bmatrix} 1 & 0 & 1 & 2 \\ 1 & 1 & 0 & 0 \\ 0 & 2 & 1 & 0 \\ 0 & 2 & 0 & 2 \end{bmatrix}$$

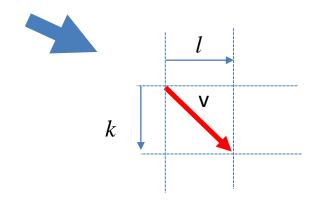
$$P_{11} = \frac{1}{9} \quad \begin{bmatrix} 2 & 0 & 1 \\ 1 & 2 & 2 \\ 1 & 0 & 0 \end{bmatrix}$$



### Definition of the Co-ocurrence Matrix

$$P_{kl}(i,j) = \frac{1}{nm} \mathop{\tilde{\bigcirc}}_{p=1}^{n} \mathop{\tilde{\bigcirc}}_{q=1}^{m} \mathop{\tilde{\bigcirc}_{q=1}^{m}} \mathop{\tilde{\bigcirc}_{q=1}^{m}}_{q=1}^{m} \mathop{\tilde{\bigcirc}_{q=1}^{m}}$$

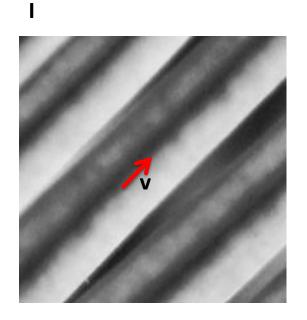
Vector v

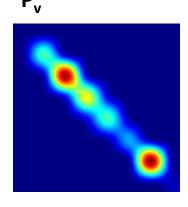


What happens if the diagonal of the co-occurrence matrix is high?

That means, that in the selected direction the pixel values do not change significantly.

In this direction the pixel values do not change significantly.

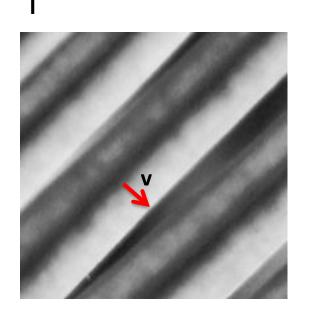


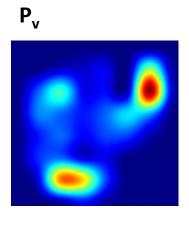


What happens if the diagonal of the co-occurrence matrix is low?

That means, that in the selected direction the pixel values do change significantly.

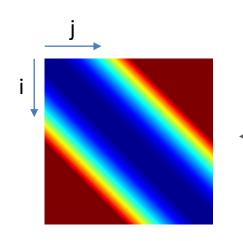
In this direction the pixel values do change significantly from low to high and from high to low.

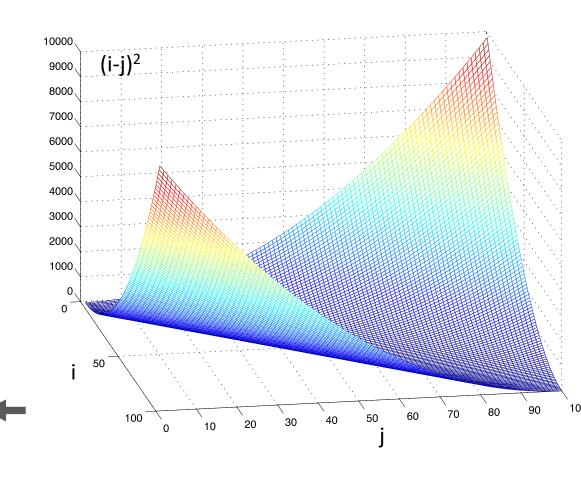




## Contrast

$$I_{kl} = \sum_{i=1}^{N_x} \sum_{j=1}^{N_x} (i-j)^2 P_{kl}[i,j]$$

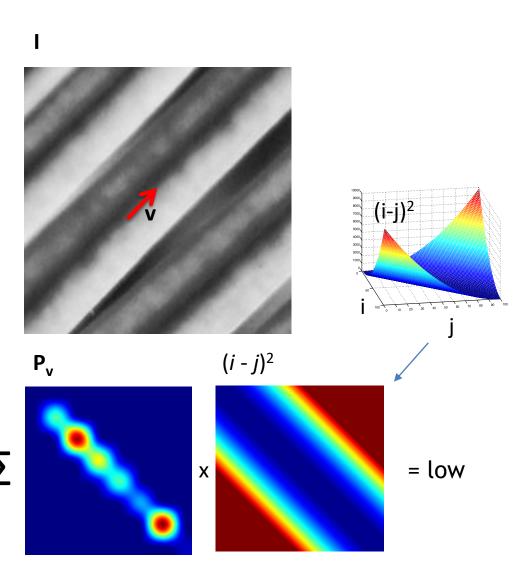




In this direction the pixel values do not change significantly.

Contrast

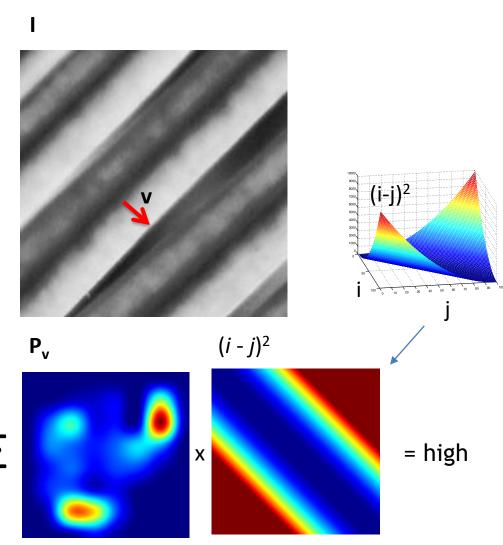
$$I_{kl} = \sum_{i=1}^{N_x} \sum_{j=1}^{N_x} (i-j)^2 P_{kl}[i,j]$$
 =  $\sum$ 



In this direction the pixel values do change significantly from low to high and from high to low.

Contrast

$$I_{kl} = \sum_{i=1}^{N_x} \sum_{j=1}^{N_x} (i-j)^2 P_{kl}[i,j]$$
 =  $\sum$ 



# Features based on Co-occurrence Matrix

$$I_{kl} = \sum_{i=1}^{N_x} \sum_{j=1}^{N_x} (i-j)^2 P_{kl}[i,j]$$

Moment of inverse difference 
$$Z_{kl} = \sum_{i=1}^{N_x} \sum_{j=1}^{N_x} \frac{P_{kl}[i,j]}{1+(i-j)^2}$$

$$E_{kl} = \sum_{i=1}^{N_x} \sum_{j=1}^{N_x} [P_{kl}[i,j]]^2$$

$$H_{kl} = \sum_{i=1}^{N_x} \sum_{j=1}^{N_x} P_{kl}[i, j] \log(P_{kl}[i, j])$$

## Features based on Co-occurrence Matrix

Angular second moment:  $f_1 = \sum_{i=1}^{N_x} \sum_{j=1}^{N_x} [p(i,j)]^2$ 

Contrast:  $f_2 = \sum_{n=0}^{N_x-1} n^2 \sum_{i=1}^{N_x} \sum_{i=1}^{N_x} p(i,j) \text{ for } |i-j| = n$ 

Correlation:  $f_3 = \frac{1}{\sigma_x \sigma_y} \sum_{i=1}^{N_x} \sum_{j=1}^{N_x} \left[ ij \cdot p(i,j) - \mu_x \mu_y \right]^2$ 

Sum of squares:  $f_4 = \sum_{i=1}^{N_x} \sum_{j=1}^{N_x} (i-j)^2 p(i,j)$ 

Inverse difference moment:  $f_5 = \sum_{i=1}^{N_x} \sum_{j=1}^{N_x} \frac{p(i,j)}{1+(i-j)^2}$ 

Sum average:  $f_6 = \sum_{i=2}^{2N_x} i \cdot p_{x+y}(i)$ 

Sum variance:  $f_7 = \sum_{i=2}^{2N_x} (i - f_8) \cdot p_{x+y}(i)$ 

Sum entropy:  $f_8 = -\sum_{i=2}^{2N_x} p_{x+y}(i) \cdot \log(p_{x+y}(i))$ 

Entropy:  $f_9 = -\sum_{i=1}^{N_x} \sum_{j=1}^{N_x} p(i,j) \log(p(i,j))$ 

Difference variance:  $f_{10} = var(\mathbf{p}_{x+y})$ 

Difference entropy:  $f_{11} = -\sum_{i=0}^{N_x-1} p_{x-y}(i) \cdot \log(p_{x-y}(i))$ 

Information measures of correlation 1:  $f_{12} = \frac{f_9 - HXY1}{\max(HX, HY)}$ 

Information measures of correlation 2:  $f_{13} = \sqrt{1 - \exp(-2(HXY2 - HXY))}$ 

Maximal correlation coefficient:  $f_{14} = \sqrt{\lambda_2}$ 

where  $\mu_x$ ,  $\mu_y$ ,  $\sigma_x$  and  $\sigma_y$  are the means and standard deviations of  $p_x$  and  $p_y$  respectively with

$$p_{x} = \sum_{j=1}^{N_{x}} p(i,j)$$

$$p_{y} = \sum_{i=1}^{N_{x}} p(i,j)$$

$$p_{x+y}(k) = \sum_{i=1}^{N_{x}} \sum_{j=1}^{N_{x}} \sum_{i=1}^{N_{x}} p(i,j) \text{ for } k = 2,3,...2N_{x}$$

$$p_{x-y}(k) = \sum_{i=1}^{N_{x}} \sum_{j=1}^{N_{x}} \sum_{j=1}^{N_{x}} p(i,j) \text{ for } k = 0,1,...N_{x} - 1$$

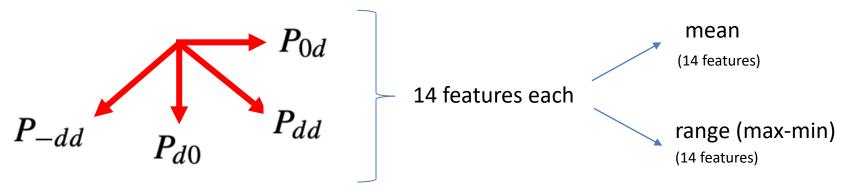
and

$$HX = -\sum_{i=1}^{N_x} p_x(i) \log(p_x(i))$$
 $HY = -\sum_{j=1}^{N_x} p_y(j) \log(p_y(j))$ 
 $HXY1 = -\sum_{i=1}^{N_x} \sum_{j=1}^{N_x} p(i,j) \log(p_x(i)p_y(j))$ 
 $HXY2 = -\sum_{i=1}^{N_x} \sum_{j=1}^{N_x} p_x(i)p_y(j) \log(p_x(i)p_y(j))$ 

In  $f_14$ ,  $\lambda_2$  is the second largest eigenvalue of Q defined by

$$Q(i,j) = \sum_{k=1}^{N_x} \frac{p(i,k)p(j,k)}{p_x(i)p_y(k)}$$

For a given 'd' in pixels, we extract 4 co-occurrence matrices:



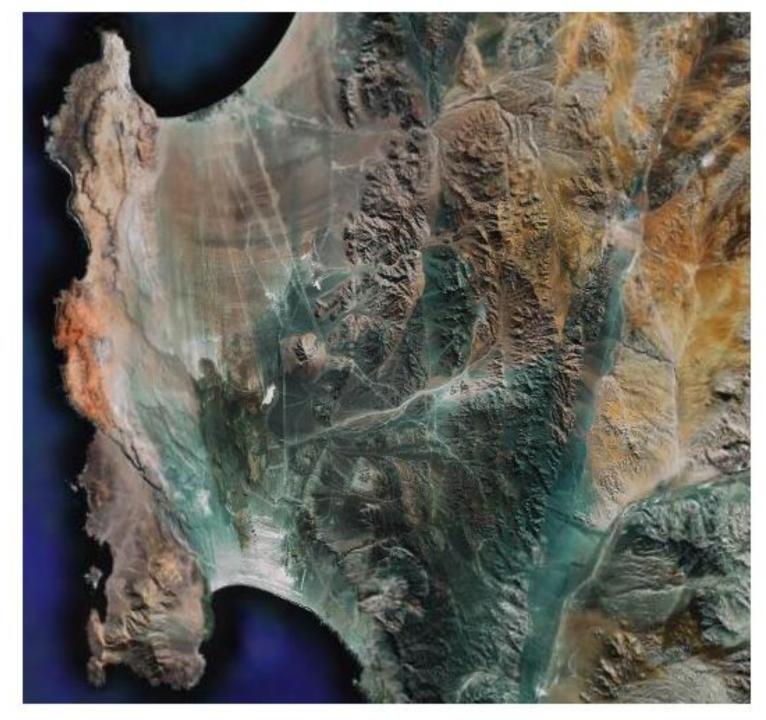
The texture features are extracted for four directions (0°-180°, 45°-225°, 90°-270° and 135°-315°) in different distances  $d = \max(k, l)$ . That is, for a given distance d we have four possible co-occurrence matrices:  $P_{0d}$ ,  $P_{dd}$ ,  $P_{d0}$  and  $P_{-dd}$ . For example, for d = 1, we have (k, l) = (0, 1); (1, 1); (1, 0); and (-1, 1). After Haralick, 14 texture features using each co-occurrence matrix are computed and the mean and range for each feature are calculated, i.e., we obtain  $14 \times 2 = 28$  texture features for each distance d. The features will be denoted as  $\bar{f}_i$  for the mean and  $f_i^{\Delta}$  for the range, for  $i = 1 \dots 14$ .

## Example

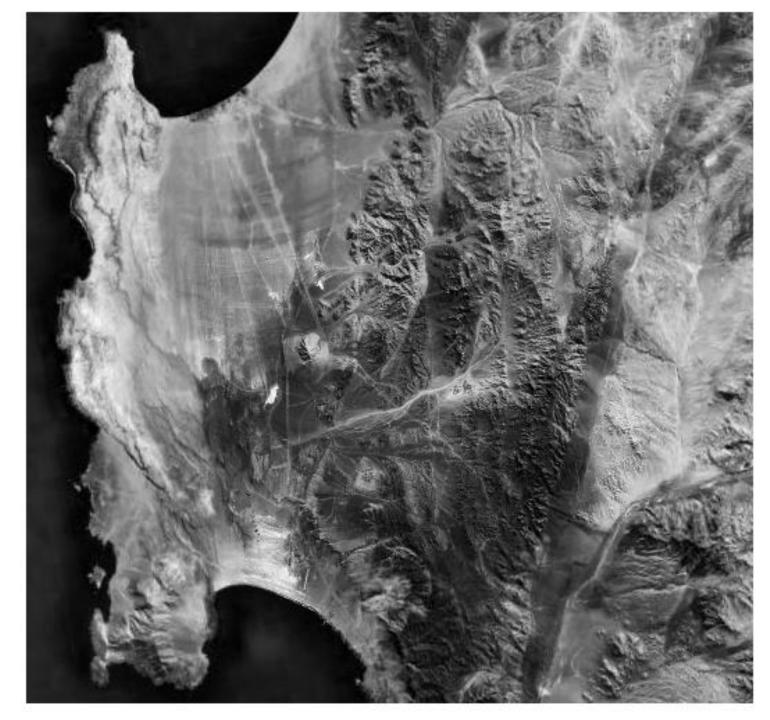
Detection of mountains and desert areas



## Original

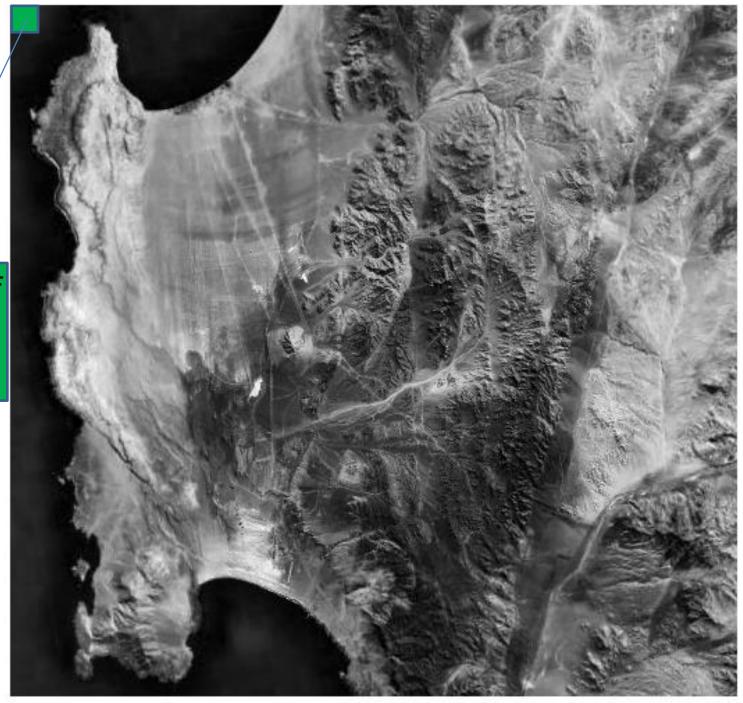


Red channel

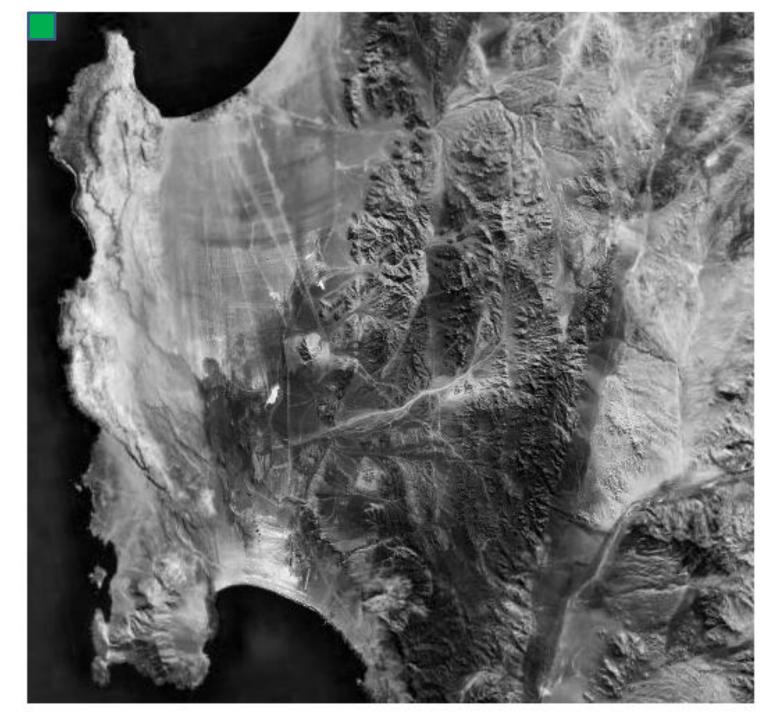


Red channel

Extraction of Haralick Features



Red channel

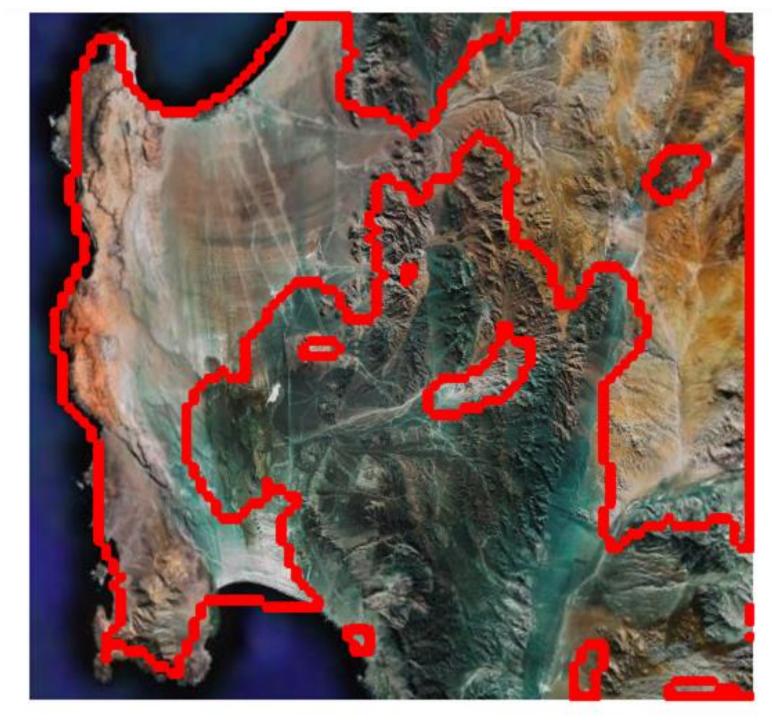


Sum Variance

Sum Variance > Threshold

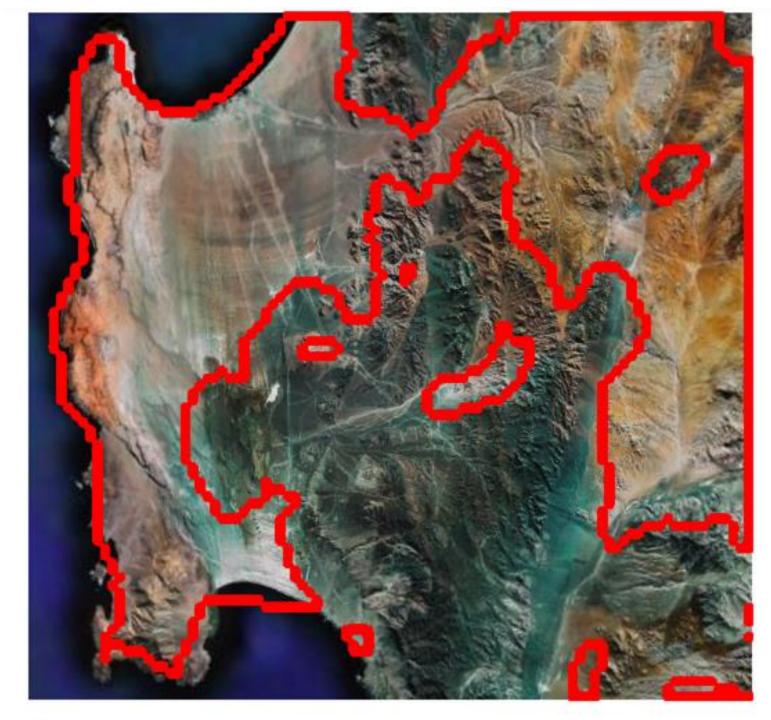


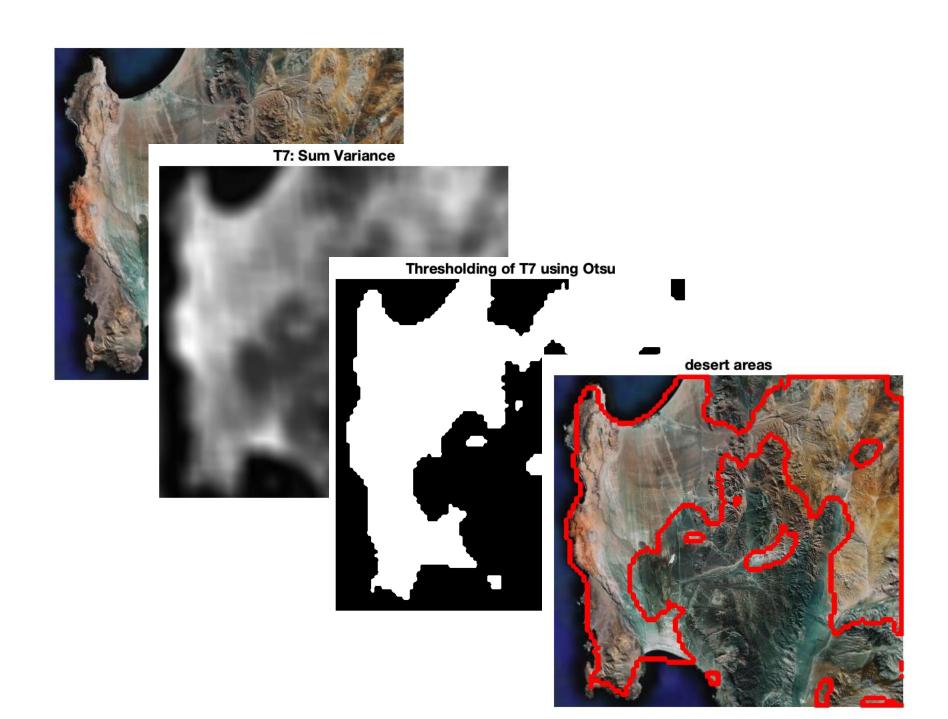
Sum Variance > Threshold



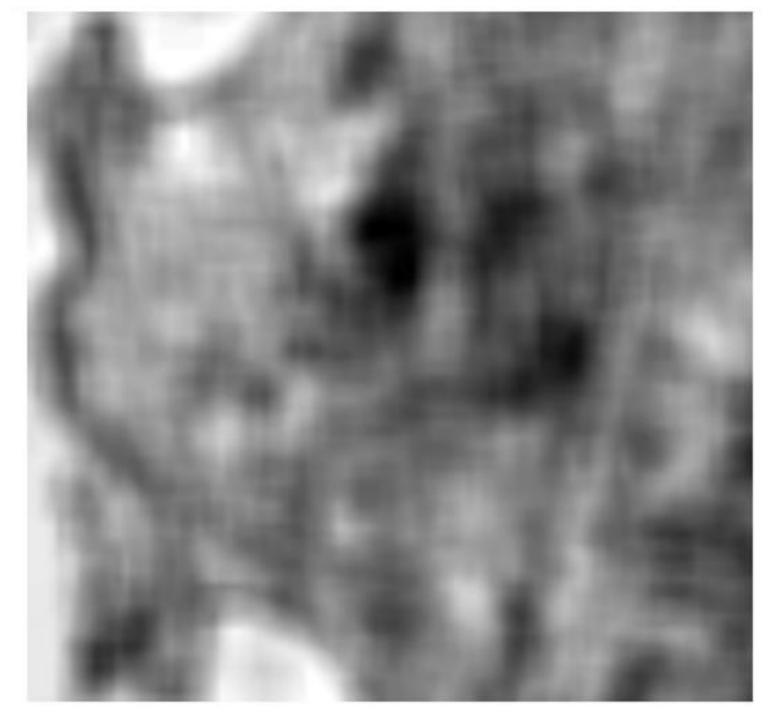
Sum Variance > Threshold

> = desert areas





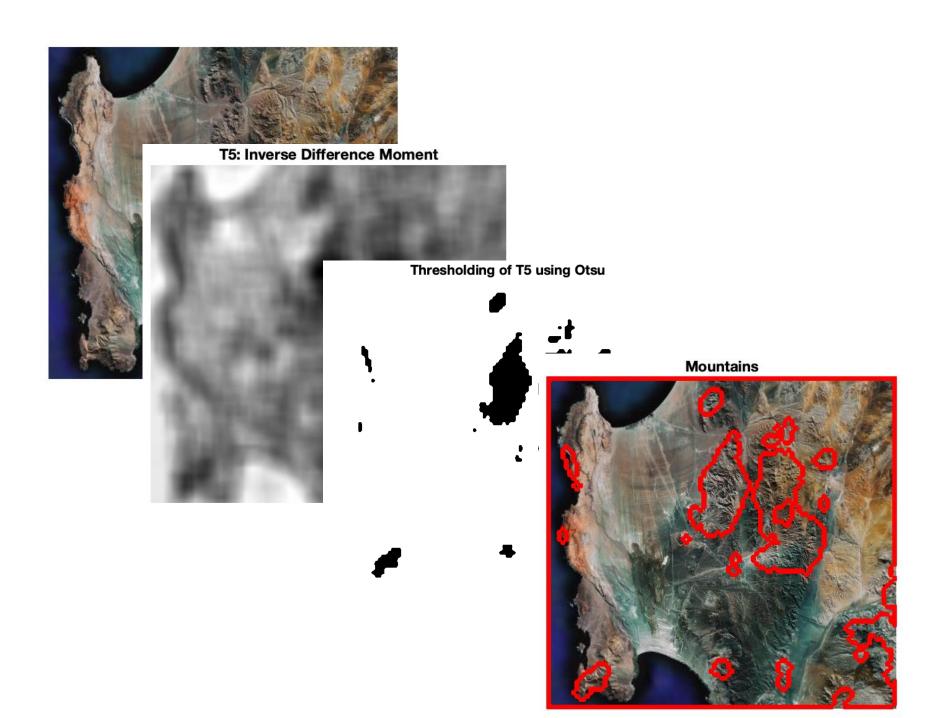
Inverse Moment Difference



Inverse Moment Difference < Threshold

= Mountains







desert areas



Mountains

